APPLICATION OF IMAGE PROCESSING FOR DETECTION OF CORROSION USING GROUND PENETRATING RADAR

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ABSTRACT
Corrosion of reinforcement concrete structure is a main cause of structural damage that required to repair or replacement. A non-destructive testing (NDT) method to find out the location and degree of corrosion-induced damage is needed. The NDT of ground penetrating radar (GPR) method has been found to be useful to evaluate reinforced concrete structure existences for the continued use or for the repair. This paper presents the study to detect the corrosion using GPR based on image processing technique and artificial neural network (ANN). A method using direct current (DC) power supply with 5% sodium chloride (NaCl) solution is employed for accelerating reinforcement bars (rebars) corrosion before rebars are induced to the reinforced concrete 1 x 1 x 0.3 m mixture. The rebars are corroded in 4 duration of exposure time (0, 1, 3, and 7 days). The 2 GHz of GPR are used for corrosion detection in the reinforced concrete slabs after 28-days of standards moist curing. The GPR data is processed and analyzed by using image processing and ANN, respectively. The result is shown that the corrosion can be detected with 100% of accuracy.

Keywords: NDT, GPR, accelerated corrosion, image processing, and ANN.

1 INTRODUCTION
Corrosion of the steel rebar is the greatest factor in limiting the life expectancy of reinforced concrete structures. The corrosion is caused either due to diffusion of the chloride ions to the steel surface or due to carbonation of concrete. In addition, the corrosion of the steel rebars and the subsequent cracking of concrete due to the ingress of chloride ions to the steel surface is more predominant than due to carbonation of concrete [1]. To assess the condition of corrosion in the concrete structure, a number of non-destructive testing (NDT) methods have been recently studied.

Some NDT methods widely were used to test the likelihood of rebar corrosion, like half-cell potencial. However, the test did not allow the detection of corrosion in a direct way. The test only provides a condition of corrosion activity. In addition, in some cases on the possible presence of damage is detected when this corrosion is in the advanced stage. Based on these conditions, engineers prefer to use the ground penetrating radar (GPR) technique. This choice was justified by the fact that this electromagnetic technology makes it possible to collect the data in a fast way. Unfortunately, the GPR technique was not yet finally accepted by engineers because its reliability to the detection of corrosion is not satisfactory [2].

The GPR is becoming more and more popular as a concrete inspection method. The GPR is significant technology for locating embedded targets in concrete. The NDT method of the GPR allows a reliable and efficient inspection of the structural integrity of reinforced concrete [3]. However, the results of GPR is very difficult to interpret and may require the skills of an experienced operator and the use of lengthy manual post-processing and subjective expertise to produce a reliable end result [4-8].

Recent years, many automatic techniques have been developed for interpreting the GPR data. Neural network, signal and image processing techniques have employed to provide a high resolution image, accurate depth and location information, and facilitate straightforward data interpretation. However, the success is so far limited to straightforward cases such as buried object location [9, 10].
Therefore, in this paper, we investigate the corrosion in concrete structures by proposing the usage of image processing techniques to obtain the best interpretation for corrosion detection and to extract features from the GPR data. The features differentiate the corrosion degree of the concrete structures. In addition, for the further process the usage of artificial neural network (ANN) for decision of data whether corrosion or no corrosion is applied.

2 LITERATURE, MATERIAL AND METHODS

2.1 GPR Applications in image processing and ANN

The strength of GPR for involving the transmission of electromagnetic waves into a material is under investigation. The reflections of these waves at interfaces and objects within the material have been analyzed to determine the location or depth of these interfaces and buried objects, and to determine the properties of the material. Mostly, GPR is utilized in reflection mode which a signal is emitted via an antenna into the structure below investigation. The arrival time and the simplicity of reflected signals caused by replacement in material properties is written and examined.

Study done by [9] had developed system comprises a neural network classifier, a pattern recognition stage, and additional pre-processing, feature-extraction and image processing stages to provide a high-resolution image of the sub-surface in near real-time facilitating straight forward data interpretation and providing accurate depth and azimuth location information of the rebars. In addition, [11] had developed guidelines and recommendations for GPR data acquisition and interpretation. By combining information extracted from various cues from within the data in a manner that minimizes the reliance on ready-made assumptions, rules of thumb and conjecture, it is possible to improve the reliability and accuracy of the final interpretation result.

In [12], the authors had achieved by subjecting GPR radargrams to a series of image processing stages followed by a curve-fitting procedure specifically developed for hyperbola. The fitting technique was applied on a variety of real hyperbolic signatures that were collected from a controlled test site. They had obtained the results indicating that this technique was fully capable of successfully estimating the depth and radius to within 10%, which validates the method and justify the used assumptions. Whereas, [13] had showed that the use of a multilayered perceptron (MLP) neural network approach could be quite effective in automating the identification and location of embedded steel reinforcing bars from a GPR investigation. Accurate estimation of depth, or cover, requires a reliable knowledge of the dielectric properties of the concrete, and recent work using a specially developed wideband horn antenna for direct determination of in situ properties was also outlined.

In [14], the authors had aimed at detecting and characterizing inclusions in concrete structures by inverting GPR data. Moreover, with 99.99% of the original variance the data needs only 139 dimensions. This dimensional reduction can make the ANN training easier and faster. The ANN were trained to find the buried inclusions characteristic and considering a non-homogenous host medium by inverting the pre-processed data. The results show that the expected maximum error was kept under 1%, which is a remarkable result, since the host medium is non-homogenous.

2.2 Sample Preparation and Data Acquisition

In this paper, the reinforced concrete slab dimension \( l = 1 \text{ m}, w = 1 \text{ m}, \) and \( h = 0.3 \text{ m} \) have prepared. The concrete grade is C30. Portland cement, uncrushed sand, crushed limestone with a maximum aggregate size of 20 mm were used to prepared the concrete mixture. Details of the mixture proportions are given in Table 1. The \( y \)-type reinforced bars (rebars) with length approximately 1 m and with diameter is 20 mm are selected.

<table>
<thead>
<tr>
<th>Concrete Mixtures</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density (kg/m³)</td>
<td>2430</td>
</tr>
<tr>
<td>Cement Content (kg/m³)</td>
<td>380</td>
</tr>
<tr>
<td>W/C</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 1. Concrete Mixture Proportions

At first, the rebars is immersed in a solution of 5% NaCl (0, 1, 3, and 7 days of exposure time) using DC power supply. The direction of current was adjusted and the defined the corroding rebars as the anode while a bar facing the corroding rebars are defined as the cathode. The current of 10V

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(volt) and 1A (ampere) were applied in the corrosion process. During the corrosion process, the electric current should be kept constant. The process was continued until the rebars corroded with different levels. The actual corrosion level for 20 mm rebar was measured as the mass loss of the bars before and after corrosion testing [15]. The corrosion level is no corrosion, low, middle, and high corrosion. In the last part, the corroded rebars are induced to concrete mixture.

The 2 GHz of GPR manufactured by IDS (Ingegneria Dei Sistemi S.p.A) Italy, were used for detection the corrosion in reinforced concrete slabs after 28-days of standard moist curing. The result could be proposed in a-scan, b-scan, c-scan, and 3D image as tabulated in Figure 1. In this paper we used 3D image as GPR data for corrosion detection. The 3D image of the GPR data showed that the corrosion can be detected only for high corrosion. However, the GPR data cannot show for low and middle corrosion because the image is not clear, as shown in Figure 2.

2.3 Image Processing Techniques

There are large number applications of image processing in diverse spectrum of human activities i.e. cancer detection in biomedical images, computer science, aggregate shape recognition in material, faulty component identification, remotely sensed scene interpretation. Imaging of concrete structures have presented many challenges due to the fact that concrete is a non-homogeneous material [16].

In this paper, we use two image processing technique i.e. k-means clustering, and edge detection to detect and investigate corrosion and non-corrosion image from GPR data of concrete structures.

K-Means Clustering

Segmentation using k-means clustering refers to the process of partitioning a digital image into multiple segments. The image segmentation results can be used to derive region-wide color and texture features, which in turn, together with the segment location, boundary shape, and region size, can be used to extract semantic information [17]. The goal of this technique is to simplify the representation of an image into something that is more meaningful and easier to analyze. The result of image segmentation is a set of segments that collectively cover the entire image. Each of the pixels in a region are similar with respect to some color characteristics [18].

In this work the algorithm of color based segmentation using k-means clustering was applied using Matlab 7. The data given by GPR is clustered by the k-means method, which aims to partition the points into k groups of color images.

![Figure 1. The results of GPR: (a) Typical A-scan, (b) Typical B-scan, (c) C-Scan, and (d) 3D image.](image-url)
Figure 2. The 3D image of GPR.

**Edge Detection**

Edge detection is a kind of method of image segmentation based on range non-continuity. Edge always appears in two neighboring areas having different grey level. It exists between object and background, object and object, region and region, and between element and element [19]. This study uses Sobel edge detector for convolution the GPR data images. This edge detector have two masks for producing edge image. The edge image is used to detect an edge in k-means clustering images of the GPR data.

The Sobel operator counts the edge using weighted for 4 neighborhoods [20]. The Sobel operator can process those images with lots of noises and gray gradient well. We order that:

\[
S_x = \begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix}
\]

\[
S_y = \begin{bmatrix}
1 & 2 & 1 \\
0 & 0 & 0 \\
-1 & -2 & -1
\end{bmatrix}
\]

\[
M = \sqrt{S_x^2 + S_y^2} \tag{1}
\]

The direction of this point is :

\[
\alpha(x, y) = \tan^{-1}\left(\frac{S_x}{S_y}\right) \tag{2}
\]

The original image of GPR data, k-means clustering image, binary image, and the edge detection drawing of Sobel operator gained using Matlab 7 simulation are shown in Figure 3.

Figure 3. (a) GPR data, (b) K-means clustering image, (c) binary image and (d) Sobel edge image.

**2.4 Artificial Neural Network (ANN)**

The most commonly ANN used for pattern recognition and classification is a multilayer perceptron (MLP) network. MLP network with m outputs and n_h hidden nodes can be expressed in the equation (3):

\[
y_j(t) = \sum_{i=1}^{n_i} w_{ij}^1 F\left[\sum_{k=1}^{n_h} w_{jk}^2 y_k(t) + b_j^2\right], \tag{3}
\]

for \(1 \leq j \leq n_h\) and \(1 \leq k \leq m\)

where \(w_{ij}^1\) and \(w_{jk}^2\) denote the weights of the connection between input and hidden layer and the connection between hidden and output layer, respectively. \(b_j^1\) and \(b_j^2\) denote the thresholds in hidden nodes and inputs that are supplied in the input layer, respectively; \(n_i\) and \(n_h\) are the number of input nodes and hidden nodes respectively. \(F(\cdot)\) is an activation function that is normally selected as a sigmoidal function [22]. The MLP model is shown in Figure 4.
The input layer, hidden layer, and output layer compiled up to down respectively. In this current study we use 4 features i.e. sum of white pixels, sum of black pixels, area of rebar, and perimeter of rebar of the GPR image data as input data fed into MLP network and two outputs i.e. high corrosion and no corrosion. Four features were obtained from processed images which images segmented were taken no corrosion and high corrosion separately with size 100x200 pixels as shown in Figure 5.

Features extractions for sum of black pixels and white pixels (area) were calculated based on binary image as shown in Figure 3(c). However, perimeter of object was calculated based on Sobel edge image as shown in Figure 3(d). Before the features of GPR data is fed into MLP network, the data was normalized and arranged using 10 fold cross validation. Data classification is tabulated in Table 2. Thus, ten datasets were used to show range of classification results for corrosion and no corrosion.

<table>
<thead>
<tr>
<th>Trainset</th>
<th>Testset</th>
</tr>
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<tbody>
<tr>
<td>Corrosion</td>
<td>90</td>
</tr>
<tr>
<td>No corrosion</td>
<td>27</td>
</tr>
<tr>
<td>Total</td>
<td>117</td>
</tr>
<tr>
<td>Total data</td>
<td>130</td>
</tr>
</tbody>
</table>

3 RESULTS

All data were obtained from GPR scans of sample in concrete laboratory civil engineering Universiti Sains Malaysia (USM). The allocations for training and testing has showed in Table 2 with ten datasets. As mentioned before, four features were extracted from each data image as input fed into the MLP network. The MLP network trained with Levenberg-Marquardt (LM) Backpropogation were used for training ten datasets.

For this result section, we presented the classification performances based on accuracy of the MLP network for showing the capability of GPR data to detect high corrosion and no corrosion in concrete structure. The results are showed that all of the ten datasets performed excellent classification with all datasets accuracies value 100% for training and testing as tabulated in Table 3.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Epoch</th>
<th>Hidden</th>
<th>AccTrain</th>
<th>AccTest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train1</td>
<td>42</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train2</td>
<td>8</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train3</td>
<td>5</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train4</td>
<td>14</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train5</td>
<td>9</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train6</td>
<td>9</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train7</td>
<td>8</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train8</td>
<td>8</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train9</td>
<td>17</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Train10</td>
<td>10</td>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

From Table 3, according to hidden nodes and epoch nodes used by the MLP network, we analyses that these data are not complicated data due to high accuracy performance of the MLP network classification. Most probably, these results are influenced by effective image processing technique.
for segmentation the object of interest and other object in images.

4 CONCLUSIONS AND DISCUSSIONS

This paper presented the observation of GPR data with two conditions of concrete structures. Image processing techniques are used to pre-process the image data to obtain features in order to classify the image into two class using ANN fast, clearly and easily. The general accuracy results presented in Table has proven to be effective for detecting the corrosion and no corrosion in concrete structures using GPR data. The main advantage of ANN for classification is fast and better results than other statistic tools especially the complicated data. The authors of this paper believe that the used techniques could be used to classify the other damage images.

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REFERENCES


